New Regression Model to Estimate Global Solar Radiation Using Artificial Neural Network

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Abstract

The main objective of the present study was to develop a new model for the solar radiation estimation in hilly areas of North India for the determination of constants 'a' and 'b' by taking only latitude and altitude of the place into consideration. In this study, new model was developed based on Angstrom-Prescott Model to estimate the monthly average daily global solar radiation only using sunshine duration data. The monthly average global solar radiation data of four different locations in North India was analyzed with the neural fitting tool (nftool) of neural network of MATLAB Version 7.11.0.584 (R2010b) with 32-bit (win 32). The neural network model was used with 10 hidden neurons. Eight months data was used to train the neural network. Two months data was used for the validation purpose and the remaining two months for the testing purpose. The new developed model estimated the values of 'a' which range from 0.209 to 0.222 and values of 'b' ranging from 0.253 to 0.407. The values of maximum percentage error (MPE) and mean bias error (MBE) were in good agreement with the actual values. Artificial neural network application showed that data was best fitted for the regression coefficient of 0.99558 with best validation performance of 0.85906 for Solan. This will help to advance the state of knowledge of global solar radiation to the point where it has applications in the estimation of monthly average daily global solar radiation.

Keywords

Artificial Neural Network; Global Solar Radiation; Extraterrestrial Radiation; Solar Constant; Sunshine Hour

Research Highlights

- Development of new model for solar energy estimation

- Use of Artificial Neural Network to analyze global solar radiation

- Regression coefficient representation

- Graphical representation of the best validation performance

Introduction

Solar radiation data are required in different areas, such as solar water heating, wood drying, stoves, ovens, photovoltaic, atmospheric energy balance studies, thermal load analyses on buildings, agricultural studies, and meteorological forecasting which should be reliable and readily available for design, optimization and performance evaluation of solar technologies for any particular location as given by Bezir *et al.* (2010) and El-Sebaii *et al.* (2010). Compared to measurements of other meteorological variables, the measurement of solar radiation is more prone to errors and often encounters more problems such as technical failure and operation related problems given by Tang *et al.* (2010). These problems could be one of many: calibration problems, problems with dirt on the sensor, accumulated water, shading of the sensor by masts, etc. Even at stations where global solar radiation is observed, there could be many days when global solar radiation data are missing or lie outside the expected range due to these equipment failures and other problems as given by Rahimikhoob (2010). Nevertheless, for many developing countries, solar radiation measurements are not easily available because of the incapability to afford the measuring equipments and techniques involved as given by Bezir *et al.* (2010). Therefore, it is necessary to develop methods to predict solar radiation from the available meteorological data.

Himachal Pradesh is located in north India with Latitude 30º 22' 40" N to 33º 12' 40" N, Longitude 75º 45' 55" E to 79º 04' 20" E, height (From mean sea Level) 350 meter to 6975 meter and average rainfall 1469 mm. The study has been initiated by introducing different

models by taking sunshine hour duration under consideration. The very first equation was given by Angstrom in 1924; and Angstrom's regression coefficients 'a' and 'b' have important physical interpretations with respect to the total insolation reaching the earth's surface at any place. The coefficient 'a' is supposed to be related to the percentage of extra terrestrial insolation reaching the earth's surface on a completely cloud covered day that is the diffuse radiation while 'b' is related to the percentage of extra terrestrial insolation absorbed by the clouds on such a day. The estimated value of G obtained for any station, therefore, depends on the accuracy with which these coefficients are determined which is neither a very accurate nor a very convenient way to calculate mean daily solar radiation and the exact evaluation of daily global radiation with a cloud free atmosphere is difficult. This obstacle is removed by Prescott (1940) by means of amending the equation and replacing daily global radiation with a cloud free atmosphere with daily total extra terrestrial solar radiation on a horizontal surface. Prescott (1940) replaced G_0 (monthly average daily extraterrestrial solar radiation) with the daily total extra terrestrial solar radiation on a horizontal surface (ETR). The new regression had the form

$$\frac{G}{ETR} = (a + b)\ \frac{n}{N} \tag{1}$$

where 'a' and 'b' were the new regression parameters, established empirically for each location. Most of the investigations made so far have been based on monthly mean values of 'n' and 'G'. Typical values of 'a' published in literature range from 0.14 to 0.54 and those of 'b', from 0.18 to 0.73. The lower values of 'a' are invariably associated with higher values of 'b' and vice versa. The variability of (a + b) was much less than that of either 'a' or 'b'. According to Black et al. (1954) the regression coefficient 'b' was more or less constant while the value of 'a' showed marked variation. Glover and McCulloch (1958) concluded in their model that for all practical purposes the coefficient 'b' is considered constant. Frere et al. (1975) has used graphical relationship between the regression constants and Page (1976) has noted that for clear atmosphere the value of $\frac{G}{G_0}$ is greater for a given value of $\frac{n}{N}$. Rietveld (1978) gave a new relation between daily global radiation with a cloud free atmosphere and daily total extra terrestrial solar radiation which is

believed to be applicable anywhere in the world. In a model given by Nguyen et al. (1997) the method of least squares is used to find the value of regression coefficients. Chandel et al. (2002) used the value of 'a' and 'b' as a function of latitude and altitude of the place.

As an alternative to conventional approaches, artificial neural networks (ANNs) have been successfully applied to solar radiation estimation and instead of being programmed in the traditional way, they are trained using past history data representing the behavior of a system. Mohandes et al. (1998) estimated global solar radiation using artificial neural network and Hontoria et al. (2002) used neural network multilayer perceptron model for hourly irradiation synthetic series. Tymvios et al. (2005) conducted comparative study of Angstrom's and artificial neural network methodologies in estimating global solar radiation. Estimation of daily solar irradiation over a mountainous area using artificial neural networks was done by Bosch et al. (2008) and Lam et al. (2008) done the modeling using ANNs for different climates in China. An integrated artificial neural networks approach for predicting global radiation was taken by Azadeh et al. (2009) while a review on models of solar radiation with hours of bright sunshine was done by Bakirci (2009). Fadare (2009) done the modeling of solar energy potential in Nigeria using an artificial neural network model and assessment on diffuse solar energy under general sky condition using artificial neural network was done by Shah Alam et al. (2009). Martí and Gasque (2011) improved the temperature-based ANN models for solar radiation estimation through exogenous data assistance.

Irrespective of developing a new model, the neural fitting tool (nftool) of neural network of MATLAB Version 7.11.0.584 (R2010b) with 32-bit (win 32) used for the study is preferred compared to other statistical methods, as in statistical methods higher level of mathematics has to be solved. Due to tough calculations, the probability of error is more. Evaluation, estimation and prediction are often done using statistical packages such as SAS, SPSS, GENSTAT etc. Most of these packages are based on conventional algorithms such as the least square method, moving average, time series, curve fitting etc. The performances of these algorithms are not robust enough when the data set becomes very large. This approach is both time and mind consuming. Therefore, artificial neural network is outperforms these methods. Result of artificial neural network depends upon

number of hidden layer neurons. In order to get optimize result, optimal number of hidden layer neurons has to be selected. One way to select hidden layer neuron using optimizes algorithm technique and other way is hit and trial method which has been applied in existing proposed model. Neural networks having the potential to make better, quicker and more practical predictions than any of the traditional methods, can be used to predict energy consumption more reliably than traditional simulation models and regression techniques. Artificial neural networks are nowadays accepted as an alternative technology offering a way to tackle complex and ill-defined problems.

The neural network model was used with 10 hidden neurons. One can return to previous step and can change the number of hidden neurons if the network does not perform well after training. Here, it gave best results with 10 neurons, and depicted the validation performance by knowing mean squared error (MSE) and helped to determine the regression coefficient's value.

Material and Method

The new model developed included the effect of latitude and altitude for the four North Indian locations Solan (Himachal Pradesh) [latitude 31.1^0 N, longitude 77.1^0 E and altitude 1600 m], Palampur (Himachal Pradesh) [latitude 32.6^0 N, longitude 76.3^0 E and altitude 1270 m], Amritsar (Punjab) [latitude 31.63^0 N, longitude 74.87^0 E and altitude 234 m] and New Delhi [latitude 28.58^0 N, longitude 77.2^0 E and altitude 239 m] to calculate the regression coefficients 'a' and 'b' given by

$$a = 0.248 \, Cos \, \phi + \frac{1}{Altitude} \qquad (2)$$

$$b = 0.768 \, Sin \, \phi + \frac{1}{Altitude} \qquad (3)$$

where φ is latitude of the location

The values of a and b computed for four stations of North India have been presented in Table.5 which shows that the values of a ranges from 0.209 to 0.222 and values of b ranges from 0.253 to 0.407.

The other formulae used were given by Cooper (1969) and also used by Duffie and Beckman (1991) are:

$$G_0 = \frac{24}{\pi} \, I_{sc} \, (1 + 0.33 \, Cos \, \frac{360 \, n}{365}) \, (Cos \, \phi \; Cos \, \delta \, Sin \, W_s + $$
$$\frac{2\pi \, Ws}{360} \, Sin \, \phi \; Sin \, \delta) \qquad (4)$$

$$\delta = 23.45 \, Sin \, (360 \times \frac{284 + d}{365}) \qquad (5)$$

$$W_s = Cos^{-1} \, (-tan \, \phi \; Tan \, \delta) \qquad (6)$$

$$N = \frac{2}{15} \, W_s \qquad (7)$$

where

G_0 = Monthly average daily extraterrestrial solar radiation

N = Monthly average daily maximum number of hours of possible sunshine (or day length)

n = Monthly average daily number of hours of bright sunshine

d = day of the year (calculated on 15th of each month)

W_s = Sunset hour angle

δ = Solar declination

MSE measures the average of the squares of the errors. If $\hat{Y}$ is a vector of n predictions, and Y is the vector of the true values, then the MSE of the predictor is:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (\hat{Y_i} - Y_i)^2. \qquad (8)$$

The major three steps used to analyze the data are:

Training

This data was presented to the network during training and the network was adjusted according to its error. Eight months data was used to train the neural network.

Validation

Data was used to measure network generalizations and halt training when generalization stopped improving. Two months data was used for the validate purpose.

Testing

This data had no effect on the training and so providing an independent measure of network program during and after training. Remaining two months data was used for the testing purpose.

Jung & Yum (2011) showed that artificial neural network (ANN) learns and extracts the process behavior from the past operating information. In general, there are two types of learning: supervised and unsupervised learning. In the case of supervised learning, a set of training input vectors with the corresponding set of target vectors is trained to adjust the weights in a neural network. On the other hand, target vectors are not specified in unsupervised learning. An ANN has one or more hidden layers, whose computation nodes are correspondingly called hidden neurons of hidden units shown by Emiroglu et al. (2011). An important stage of an ANN is the training step in which the ANN is trained to return a

specific output when a specific input is given, which is   done by continued training on a set of training data.

TABLE 1 CALCULATION OF SOLAR RADIATION FOR SOLAN

Month	ETR	n	N	n/N	d	δ	Ws	G_P	G_A
JAN	11.31	5.13	11.25	0.46	15	-9.25	1.47	4.46	3.58
FEB	13.47	6.2	12.14	0.51	44	1.81	1.59	5.59	4.26
MAR	13.99	6.81	13.89	0.49	74	22.15	1.82	5.69	5.38
APR	13.00	7.1	12.73	0.56	105	9.07	1.67	5.65	6.49
MAY	11.17	7.53	10.00	0.75	135	-23.22	1.31	5.71	7.21
JUN	10.16	8.12	10.50	0.77	166	-17.94	1.38	5.28	6.87
JUL	8.68	4.11	11.94	0.34	197	-0.71	1.56	3.03	5.59
AUG	6.78	3.24	13.41	0.24	228	16.99	1.76	2.09	5.15
SEP	8.09	4.12	14.00	0.29	259	23.38	1.83	2.67	5.41
OCT	12.89	6.04	11.38	0.53	289	-7.73	1.49	5.46	5.41
NOV	12.15	6	10.16	0.59	320	-21.65	1.33	5.43	4.42
DEC	11.10	5.01	11.74	0.43	350	-3.23	1.54	4.24	3.52

TABLE 2 CALCULATION OF SOLAR RADIATION FOR PALAMPUR

Month	ETR	n	N	n/N	d	δ	Ws	G_P	G_A
JAN	12.43	5.74	11.20	0.51	15	-9.25	1.47	4.22	2.8
FEB	13.27	6	12.15	0.49	44	1.81	1.59	4.44	3.37
MAR	13.82	6.91	14.01	0.49	74	22.16	1.83	4.62	4.31
APR	9.25	8.34	12.78	0.65	105	9.07	1.67	3.47	5.24
MAY	8.87	9.38	9.88	0.95	135	-23.22	1.29	3.99	6.15
JUN	9.66	8.4	10.41	0.81	166	-17.94	1.36	3.99	5.33
JUL	8.64	4.08	11.94	0.34	197	-0.71	1.56	2.56	3.92
AUG	8.95	4.35	13.50	0.32	228	16.99	1.77	2.61	4.34
SEP	14.39	6.43	14.14	0.45	259	23.38	1.85	4.67	3.94
OCT	7.97	9.58	11.34	0.85	289	-7.73	1.48	3.37	5.08
NOV	9.67	8.45	10.04	0.84	320	-21.65	1.31	4.09	3.64
DEC	13.19	6.5	11.72	0.55	350	-3.23	1.53	4.61	2.76

TABLE 3 CALCULATION OF SOLAR RADIATION FOR AMRITSAR

Month	ETR	n	N	n/N	d	δ	Ws	G_P	G_A
JAN	12.79	6.71	11.23	0.59	15	-9.25	1.47	5.86	3.1
FEB	11.64	7.56	12.15	0.62	44	1.81	1.59	5.45	3.99
MAR	12.19	7.5	13.94	0.54	74	22.16	1.82	5.29	4.88
APR	7.18	9.34	12.75	0.73	105	9.07	1.67	3.68	6.26
MAY	9.11	8.92	9.96	0.89	135	-23.22	1.30	5.28	6.23
JUN	9.05	10.34	10.47	0.99	166	-17.94	1.37	5.59	6.6
JUL	8.47	8.73	11.94	0.73	197	-0.71	1.56	4.34	6.32
AUG	8.58	8.52	13.45	0.63	228	16.99	1.76	4.04	5.3
SEP	7.98	8.66	14.06	0.62	259	23.38	1.84	3.72	5.45
OCT	9.16	8.51	11.36	0.75	289	-7.73	1.49	4.76	4.47
NOV	10.11	8.17	10.11	0.81	320	-21.65	1.32	5.49	3.71
DEC	11.93	7.4	11.73	0.63	350	-3.23	1.54	5.63	3.01

TABLE 4 CALCULATION OF SOLAR RADIATION FOR NEW DELHI

Month	ETR	n	N	n/N	d	δ	Ws	G_P	G_A
JAN	10.32	7.6	11.32	0.67	15	-9.25	1.48	4.87	3.99
FEB	8.13	9	12.13	0.74	44	1.81	1.59	4.05	5
MAR	13.22	8.2	13.71	0.59	74	22.16	1.79	5.87	6.14
APR	10.02	8.6	12.66	0.68	105	9.07	1.66	4.75	6.94
MAY	7.73	8	10.19	0.78	135	-23.22	1.33	3.97	7.29
JUN	10.86	5.9	10.65	0.55	166	-17.94	1.39	4.65	6.54
JUL	12.93	5.8	11.95	0.49	197	-0.71	1.56	5.20	5.33
AUG	15.08	5.6	13.28	0.42	228	16.99	1.74	5.71	5.05
SEP	16.26	7	13.82	0.51	259	23.38	1.81	6.67	5.6
OCT	7.26	8.8	11.43	0.77	289	-7.73	1.49	3.69	5.36
NOV	5.38	9.2	10.33	0.89	320	-21.65	1.35	2.98	4.52
DEC	9.92	8	11.77	0.68	350	-3.23	1.54	4.71	3.84

Results and Discussion

For all the four stations data was considered for twelve months given in Table 1, Table 2, Table 3 & Table 4.

The neural network model was used with 10 hidden neurons. Fig 1, Fig 2, Fig 3 & Fig 4 didn't indicate any major problem with the training as shown below.
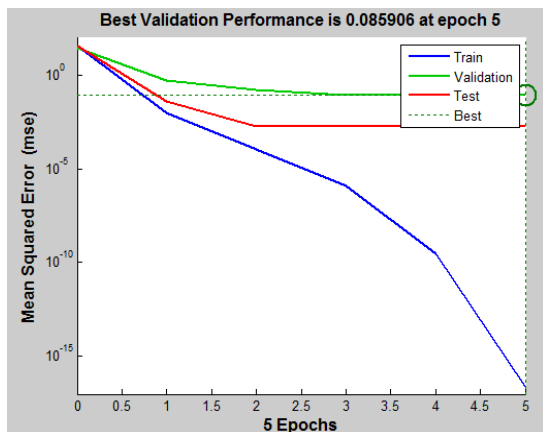

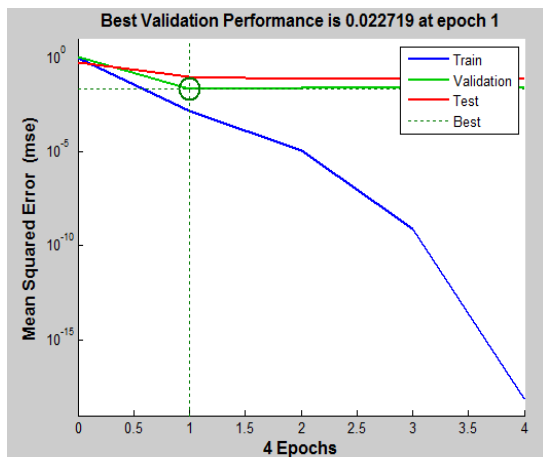FIG 1 VALIDATION PERFORMANCE OF SOLAR RADIATION FOR SOLAN

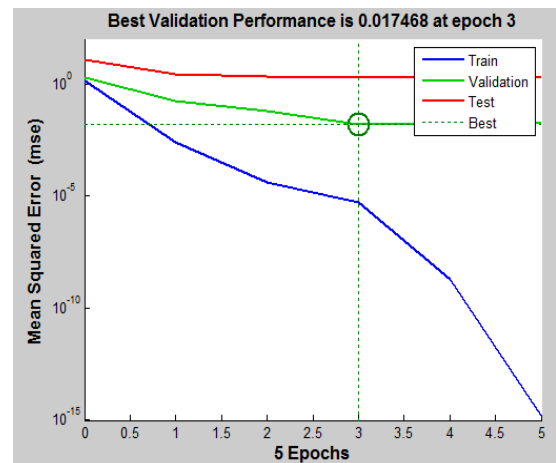FIG 2 VALIDATION PERFORMANCE OF SOLAR RADIATION FOR PALAMPUR

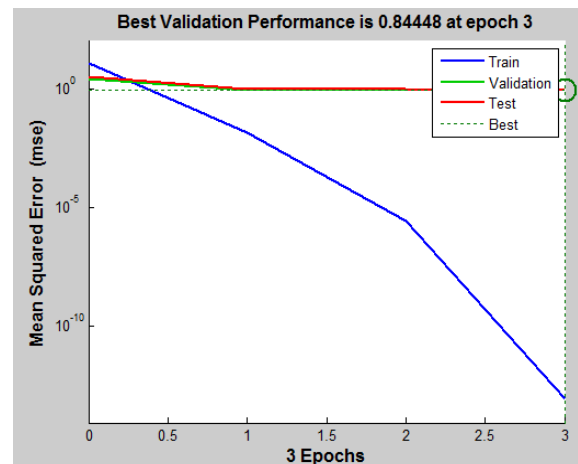FIG 3 VALIDATION PERFORMANCE OF SOLAR RADIATION FOR AMRITSAR

FIG 4 VALIDATION PERFORMANCE OF SOLAR RADIATION FOR NEW DELHI

The validation and test curves were very similar. The evaluation and validation of an artificial neural network prediction model were based upon one or more selected error matrices. The next step in validating the network was to create a regression plots

given in Fig 5, Fig 6, Fig 7 & Fig 8 which showed the relationship between the outputs of the network and the targets.
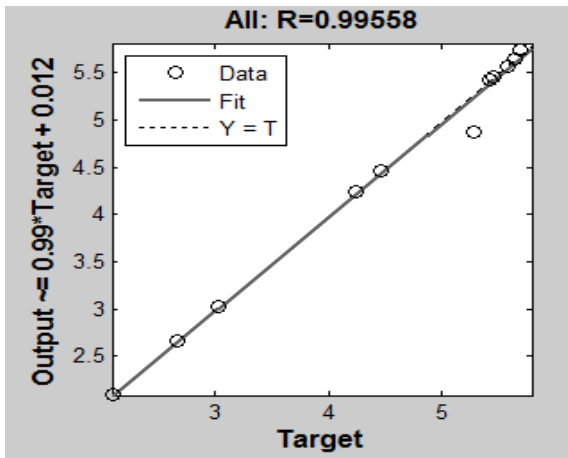

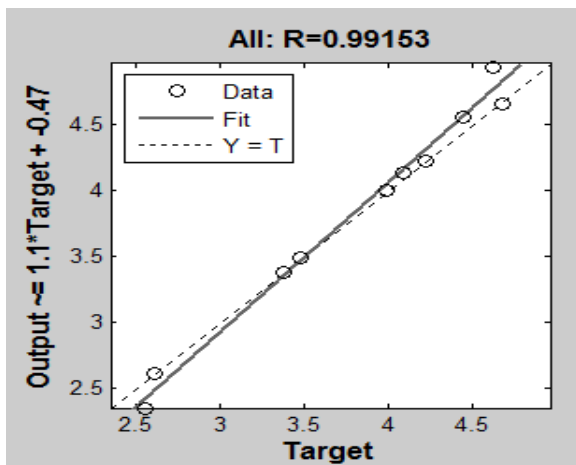FIG 5 REGRESSION ANALYSIS OF SOLAR RADIATION FOR SOLAN

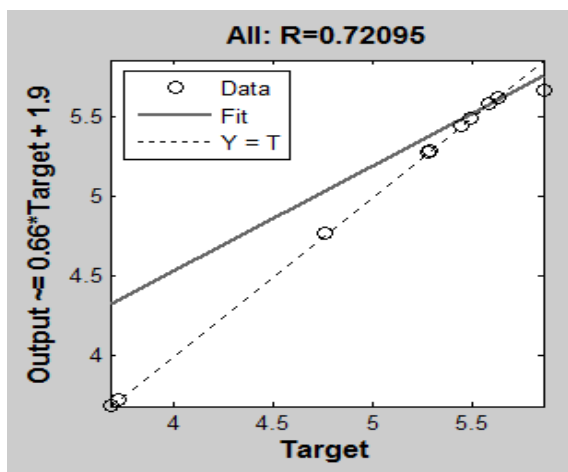FIG 6 REGRESSION ANALYSIS OF SOLAR RADIATION FOR PALAMPUR

FIG 7 REGRESSION ANALYSIS OF SOLAR RADIATION FOR AMRITSAR

Fig 1 and Fig 2 illustrate that solar radiation data is a good fit for Bajhol, Solan and Palampur with validation performance of 0.085906 having five epochs

and 0.022719 one epoch respectively as confirmed by the values of regression coefficients of 0.99558 and 0.99153 respectively for both the places depicted in Fig 5 and Fig 6.
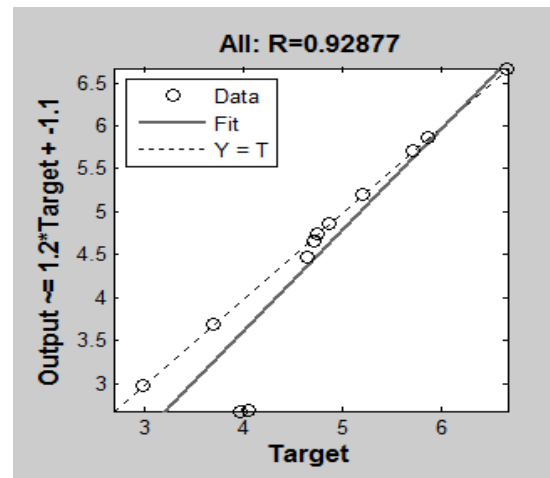

FIG 8 REGRESSION ANALYSIS OF SOLAR RADIATION FOR NEW DELHI

The solar radiation data was a slightly poor fit for Amritsar and New Delhi with validation performances of 0.017468 and 0.84448 having three epochs each as illustrated in Fig 3 and Fig 4. The same has been confirmed by the values of regression coefficients of 0.72095 and 0.92877 respectively for both the places as depicted in Fig 7 and Fig 8.

If the training were perfect, the network outputs and the targets would be exactly equal. The three axes represented the training, validation and testing data. The values of 'a' and 'b' computed for four stations of North India have been presented in Table 5 given below.

TABLE 5 CONSTANTS VALUES WITH ERRORS FOR ALL STATIONS

Stations	a	b	a + b	MPE	MBE
Solan	0.213	0.396	0.609	-8.88	-0.66
Palampur	0.209	0.253	0.462	-1.21	-0.35
Amritsar	0.216	0.407	0.623	9.79	-0.01
New Delhi	0.222	0.372	0.594	-10.01	-0.71

which showed that the values of 'a' ranges from 0.209 to 0.222 and values of 'b' ranges from 0.253 to 0.407. The dashed line in each axis represented the perfect result – outputs = targets. The solid line represented the best fit linear regression line between outputs and targets. The R value was an indication of the relationship between the outputs and targets. If R = 1, this indicated that there was an exact linear relationship between outputs and targets. If R was close to zero, then there was no linear relationship between outputs and targets.

The values of the mean bias error (MBE) and mean percentage error (MPE) are within 10 % range. Table 1 illustrated that the predicted values of the global solar radiation (G_P) for Bajhol-Solan were in good agreement with the actual values of solar radiation (G_A) except for July, August and September months. The predicted values of the global solar radiation for Palampur were in good agreement with the actual values of solar radiation except for May month (Table 2). Table 3 exemplified that the predicted values of the global solar radiation for Amritsar were in good agreement with the actual values of solar radiation except for January, April and December months. The predicted values of the global solar radiation for New Delhi were in good agreement with the actual values of solar radiation except for April and May months (Table 4).

Conclusion

The determination of global solar radiation at any site is vital for many scientific, engineering and environmental applications. In this study, a new model based on geographical data was developed to predict the global solar radiation at any place. The objective of developing a new model for the estimation of solar radiation was to review current models and to develop an alternative model that can provide a level of accuracy comparable or better than current models. An additional goal was to design a model that should be easily implemented. The present study has been successful in developing a new model for the solar radiation estimation in hilly areas for the determination of constants 'a' and 'b' by taking only latitude and altitude of the place into consideration. Although in previous models many authors have used altitude and latitude with other parameters, the formula developed in this study is more suitable, accurate and effective for the estimation of solar radiation with minimum number of parameters.

Follow up Study

The newly developed model may be used for the estimation of solar radiation in different hilly regions of India with known values of solar radiation and comparison of known and estimated value for all the stations will give the real validity of the developed model. Based on the above feedback, the model can be reframed by minute changes in the parameters.

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